Vanishing Point Detection Based on Infrared Road Images for Night Vision Navigation

Huan Wang, Feifei Li, and Mingwu Ren

Nanjing University of Science and Technology, Nanjing, P.R. China
wanghuanphd@foxmail.com, feifeili@gmail.com, renminwu@sina.com

Abstract. Road detection is important in computer vision for autonomous driving, pedestrian detection and other applications. Visible light (VL) camera is often used for daytime road detection, and infrared camera is often used for night road detection. Vanishing point (VP) detection is useful for inferring road region. Many VP detection methods have been proposed and applied successfully in VL road image. However, there is no special VP detection method for infrared road image. In this paper, we propose a VP detection approach for infrared road detection. The novelty of our approach relies on the rational assumption that the regions are very similar along the direction of the true VP. This assumption is involved in finding effective VP voters by using a non-local similarity manner, and these VP voters estimate the VP together. Quantitative and qualitative experiments show the effectiveness and efficiency of the proposed method.

Keywords: Vanishing point detection, Infrared Road detection, Non-local similarity.

1 Introduction

Road detection is an important research topic in the area of transportation systems, such as autonomous driving [1-2], driver assistance systems [3-4] and so on. Visible light (VL) camera is often used for daytime road detection [5], and infrared camera is often used for night road detection [6]. Vanishing point (VP) detection is useful for inferring road region. Many VP detection methods have been proposed and applied successfully in VL road image [7-8]. The state of the art vanishing point detection method is based on texture analysis, such as Gabor filter[9], Laplacian of Gaussian Filters[10] or edge detection [11]. However, there is no special VP detection method for infrared road image. In addition, VP detection based on texture analysis is hard for infrared images since infrared image usually has weak texture, and the edge magnitude is also small since the temperature of road and non-road region varies smoothly.

In fact, we observe that the road boundary or some of objects in a road scene usually have high similarity along the direction of VP. For a road region in an image, we can find regions similar with the region in all direction. For road boundary

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regions, we can only find high similarity along the direction of vanishing point. For some of non-road region, we can not find high similarity regions or we can find similar regions in all direction similar to the road region, for other non-road regions, we can also find similarity regions along the direction of VP similar to boundary regions. Applying this prior, we design an effective and efficient VP detection method for infrared road image. This idea is very similar to the principle of non-local similarity, which has been applied successfully in image de-noising [12] and image representation [13]. Their difference is the aim of finding several similar regions in non-local regions is to investigate their space distribution, that is, the centers of similar regions distribute in a line type or a cluttered type, other than to calculate the average of similar regions or the representation for an image patch.

The primary superiority of our method is that it needs no magnitude threshold selection for edge detection and scale parameter turning for texture analysis, instead, the intensity information of an original image is used directly.

2 Proposed Method

Our approach broadly consists of three stages: high contrast point extraction, voter point selection and vanish point voting. Below, we describe each stage in detail.

2.1 High Contrast Point Extraction

Considering road region is always in the bottom of the road image in vision navigation scene, so the first preprocessing step consists the generation of a mask that restricts the area of analysis, as shown in Fig.1(b), or we call region of interest (ROI).

Beside, computational efficiency is necessary and considered a lot, so we sample pixels where the region centered at this pixel has high contrast as processing objects, generally, these pixels and its surrounding region are very useful for VP voting. Ref.[14] proposed a simple but effective method for high contrast region extraction, it uses a simple measure of local contrast which is defined as the local standard deviation s of the image intensities divided by local mean intensity u :

$$c = \frac{s}{u} \tag{1}$$

where:

$$u = \frac{1}{w \cdot h} \sum_{i=1}^{h} \sum_{j=1}^{w} f_{ij} \tag{2}$$

$$s = \sqrt{\frac{1}{w \cdot h} \sum_{i=1}^{h} \sum_{j=1}^{w} (f_{ij} - u)^2} \tag{3}$$

w, h represent image width and height, f_{ij} is denoted as intensity of the pixel in the image coordination (i, j) we set $w = h = 11$ in our experiments.

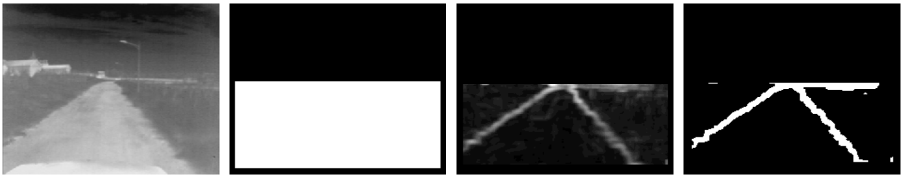
We find that this method is insensitive to image noise. We applied this method for our ROI extraction. For each pixel p_i in the ROI of original infrared image, we calculate c_i according to equation (1). Fig.1(c) show the contrast map of Fig.1(a).

Then we use calculate a threshold T to select high contrast points based on follow equations.

$$H_{p_i} = \begin{cases} 1 & \mathrm{c_i} > T \\ 0 & esle \end{cases} \tag{4}$$

$$T = \max(\varepsilon, u' + s') \tag{5}$$

where $H_{p_i} = 1$ means p_i is a high contrast point, otherwise not, u' and s' are the mean and the standard deviation of the set $\{c_i\}$ respectively, their calculation is similar to equation (2) and (3), ε is a small constant, we set $\varepsilon = 3$ in our experiments. Fig.1(d) show extracted high contrast points.



(a) (b) (c) (d)

Fig. 1. High contrast points extraction. (a) an infrared road image, (b) mask image depicting region of interest,(c) contrast map, and (c) high contrast points (white points).

2.2 Voter Point Selection

Now, a set of high contrast points are obtained, we further select points which can be used for VP voting from these high contrast points, the new selected points are called voter points.

For road image, the road pavement is always regular along the direction of VP, especially for some off-road regions. We often find that there are sidewalks, water ditch, vegetation, along the two side of the road, they are companion with the road, and they will give good inferring information for VP detection. Due to the perspective projection, these regions are distributed along the direction of VP.

In infrared image, a high contrast point being a voter point should pass following test, that is, if we search in a fixed rectangle region, which is above current high contrast point, as the white rectangles shown in Fig.2(a), we will find several similar regions. The search region and search strategy is importance, if we find similar region only in the neighborhood region of a pixel, it will lead to unbelievable result since region has local similarity. We select the most similar region in each row of the search regions (white rectangle), and we select the top N regions based on their

similarity. Generally, correlation coefficient is often used to measure the similarity of two regions:

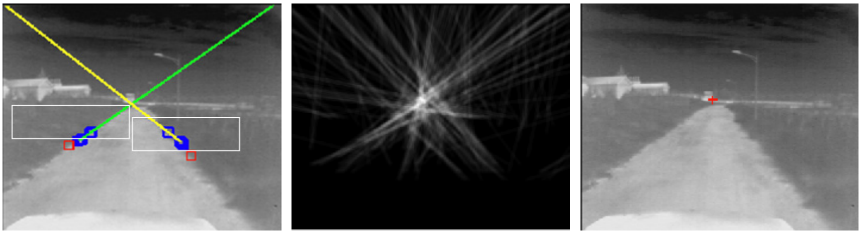
$$R(x,y)=\frac{\sum_{y=0}^{H}\sum_{x=0}^{W}(M(y,x)-\overline{M})(I(y,x)-\bar{I})}{\sqrt{\sum_{y=0}^{H}\sum_{x=0}^{W}(M(y,x)-\overline{M})^2}\sqrt{\sum_{y=0}^{H}\sum_{x=0}^{W}(I(y,x)-\bar{I})^2}} \tag{6}$$

Where M and I are two image patch, $\overline{M}$ and $\bar{I}$ are their mean respectively.

In fact, we find the absolute difference (equation (7) also works and it is more efficient than correlation coefficient.

$$dif=\sum_{y=0}^{H}\sum_{x=0}^{W}\left|M(y,x)-I(y,x)\right| \tag{7}$$

So we applied absolute difference to measure similarity. If the dif is small than threshold (we set 3 in our experiments), we consider two comparison regions are similar. After obtaining similar regions, we further judge the position relationship of center points of these regions. First, these regions should aggregate in a line type, second, the number of these regions should large than half of the selected similar regions. If the two conditions are satisfied, a voter point is found. Fig.2(a) show two regions (red rectangles) center at their voter points and their similar regions (blue rectangles).



(a) (b) (c)

Fig. 2. Vanishing point detection. (a) two regions center at their voter (red rectangles) point and their similar regions(blue rectangles), and the fitting line using center point of these similar regions (yellow and green line), (b) voting accumulation map, and (c) detected vanishing points (red points).

2.3 VP Voting

For each voter point and the center points of its non-local similar regions, we can fit a straight line use minimum distance error criteria.

$$e=\min\frac{1}{N}\sum_{\substack{(x,y)\in\\(x_i^j,y_i^j)_{j=1}^N}}\frac{|Ax+By+C|}{\sqrt{A^2+B^2}} \tag{8}$$

That is, for any two points, a straight line is fit. Then we calculate the distance error from a point (x, y) to the fit straight line equation $Ax + By + C = 0$, and average distance is obtained. The straight line which takes the minimum average distance error e is selected.

By generating an accumulation image initialized with zero, all the points in the fit straight line are accumulated in the accumulation image. The accumulation image of Fig.2(a) is shown in Fig.2(b), and then the position with maximum accumulation value in the accumulated image is considered as the VP, as shown in Fig.2(c),

3 Experiments

All the experimental data in this paper are captured by a infrared camera which is mounted in the front floor of our autonomous lane vehicle. The image resolution is 352 by 288. Some typical detection results are reported in Fig.1,where the six figures depict different scenes include two type pavement, sandstone road and cement road, and different non-road objects, such as trees, vegetations, sidewalk involved with shadows and so on. Red crossing show their VP detection results.

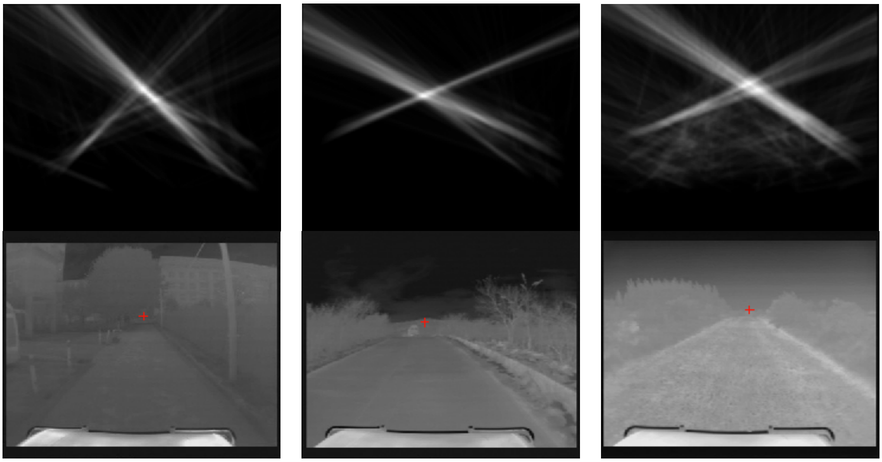


Fig. 3. Results of vanishing point detection in different road scene

We also select two state of the art VP detection methods for comparison. The two methods are proposed in Ref.[9] and Ref.[10]. One is based on Gabor filter, and the other is based on Laplacian of Gaussian Filters. It should be noted here that the two methods for comparison obtain similar results as our method for the images shown in Fig.3. However, they are not robust for other images in our database. We show some VP detection results which the two methods fail but our method succeeds in Fig.4.

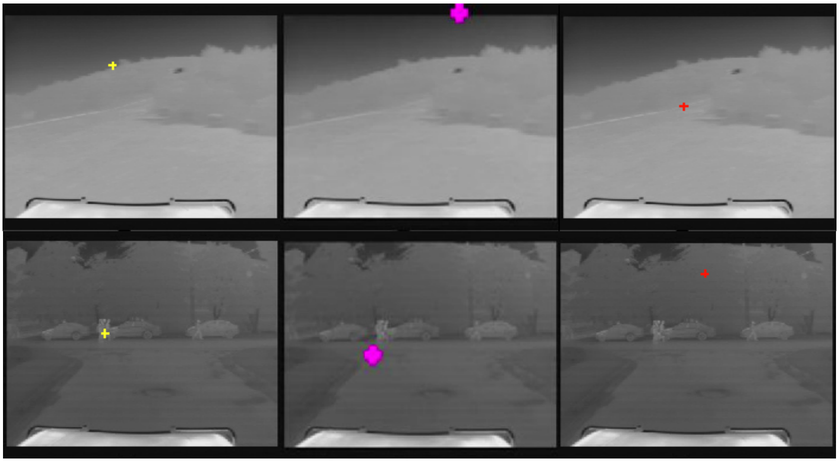


Fig. 4. Comparison of the three methods. (a) method proposed in Ref.[9], (b) method proposed in Ref.[10], (c) our method.

Finally, we test the average processing time of the three methods with more than 500 images of the dataset. All methods runs in a PC whose main configure are: CPU: AMD2.0, memory Size: 1G, and VC++6.0 develop environment is used. We coarsely compare the average processing time of the three methods in table 1. It is clearly shown that our method is more efficient.

Table 1. Comparison of Average processing time

Methods	Average time(second)
Ref.[9]	40.73
Ref[10]	20.21
Our methods	7.68

4 Conclusion

VP detection is very important and useful for road detection, most VP detection methods are proposed for visual light (VL) images in last decades and many have been demonstrated very effective for road detection. However, little literature investigates infrared image based VP detection. In essential, the VP detection methods based on VL image usually can not be used to infrared images straightforward since the texture of infrared image is very weak. This paper proposed a simple but effective approach for infrared based VP detection. Experiments on real infrared road image sequences demonstrate its effectiveness and efficiency. In the future, we will apply our VP detection method to detect road boundaries in infrared road images.

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References

1. Lookingbill, A., Rogers, J., Lieb, D., Curry, J., Thrun, S.: reverse optical flow for self-supervised adaptive autonomous robot navigation. International Journal of Computer Vision 74(3), 287–302 (2007)
2. Thorpe, C., Hebert, M., Kanade, T., Shafer, S.: vision and navigation for the Carnegie-Mellon Navlab. IEEE Trans. Pattern Analysis and Machine Intelligence 10(3), 362–373 (1988)
3. Sun, Z., Bebis, G., Miller, R.: On-road vehicle detection: A review. IEEE Transaction on Pattern Analysis and Machine Intelligence 28(5), 694–711 (2006)
4. Dollar, P., Wojek, C., Schiele, B., Perona, P.: Pedestrian detection: An evaluation of the state of the art. IEEE Transaction on Pattern Analysis and Machine Intelligence 34(4), 743–761 (2012)
5. Kong, H., Autibert, J.-Y., Ponce, J.: General Road detection from a single image. IEEE Transaction on Image Processing 19(8), 2211–2220 (2010)
6. Ren, M., Sun, H., Wang, H., Yang, J.: Road Boundary deteciton in infrared image for ALV navigation. Infrared and Laser Engineering 35(1), 106–110 (2006)
7. Alvarez, J.M., Gevers, T., Lopez, A.M.: IEEE International Conference on Computer Vision and Pattern Recognition. In: IEEE International Conference on Computer Vision and Pattern Recognition (2010)
8. Kong, H., Autibert, J.-Y., Ponce, J.: Vanishing point detection for road detection. In: IEEE International Conference on Computer Vision and Pattern Recognition (2009)
9. Moghadam, P., Starzyk, J.A., Wijesoma, W.S.: Fast vanishing-point detection in unstructed environment. IEEE Transaction on Image Processing 21(1), 425–430 (2012)
10. Kong, H., Sarma, S.E., Tang, F.: Generalizing laplacian of Gaussian Filters for vanishing point detection. IEEE Transactions on Intelligent Transportation Systems (2013)
11. Siagian, C., Chang, C.-K., Itti, L.: Mobile robot navigation system in outdoor pedestrian environment using vision-based road recognition. In: IEEE International Conference on Robotics and Automation, ICRA (2013)
12. Buades, A., Coll, B., Morel, J.-M.: A non-local algorithm for image denoising. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition (2005)
13. Wang, S., Zhang, L., Liang, Y.: Nonlocal spectral prior model for low-level vision. In: Lee, K.M., Matsushita, Y., Rehg, J.M., Hu, Z. (eds.) ACCV 2012, Part III. LNCS, vol. 7726, pp. 231–244. Springer, Heidelberg (2013)
14. Huang, K., Wang, L., Tan, T., Maybank, S.: A real-time object detecting and tracking system for outdoor night surveillance. Pattern Recognition 41(1), 432–444 (2008)